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ABSTRACT

This paper describes a quantitative model for the optimal assignment of students to courses for their complete high school careers. The model--the Automatic Curriculum Planning Program (ACPP)--can assign curriculum to a complete set of students based on their derived student grouping. Following a review of the literature on techniques for optimizing curriculum, the paper examines curriculum valuing and student classification. It then discusses ACPP's two-stage programming algorithm, which is resolved by Boolean reduction techniques. The paper concludes that quantitative models for decision-making can be useful in the selection of courses for high school students, either as a group or as individuals. When used with the statistical value generation techniques described, they can eliminate the need for tracking in schools. (Author/LD)

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Automated High School Curriculum Planning.[1]

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ABSTRACT

A quantitative model is described for the optimal assignment of students to courses for their complete high school careers. Values of curriculum, assigned by counselor-judges for types of students, are found to be highly reliable (average reliability of 0.65). Model-generated student schedules are found to be unfailing in their conformity to all of the constraints fo the test high school's curriculum. ACPP (the Automatic Curriculum Planning Program) incorporates a two-stage dynamic programming algorithm with curricular sequence constraints resolved by Boolean reduction techniques. It is found to produce student plans of study which compare favorably with those which students actually followed.

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[1]Paper presented to the Annual Meeting of the American Educational Research Association, Boston, Mass., April, 1980.

The author wishes to acknowledge the guidance of Dr. Ellis B. Page and the contributions of Professors Richard Whinfield and Marvin Rothstein and to thank David Jarjoura, Jack E. Davis and Wilson Velandia for their fine advice during various phases of the work. It would not have been possible without the continuing support of the University of Connecticut's Research Foundation, Institute for Social Inquiry (formerly the Social Science Data Center), and Research Computer Center. Portions of this paper are extracted with permission from Grandon (1979).

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INTRODUCTION

The decisions made by teachers, students, parents and school administrators all have effects on the educational system. The degree to which such decisions are made rationally is the degree to which intelligent schooling for children is to be expected. Advances in mathematical and computational modeling have aided in rationalizing educational systems. These models have been able to help decision makers ease economic burdens and hasten the processing of information. Since the introduction of computer algorithms in the 1960's, schools have been able largely to liberate themselves from the otherwise formidable task of student scheduling. Today such scheduling is completed in much less time than in the past, and with far fewer workers. And large school budgeting systems have been developed to allocate expenditures for various physical resources. Such budgeting has often used linear programming techniques. The advent of dynamic programming (DP) has still further encouraged rational approaches to educational decisions.

The present research is designed to extend rationality to the assignment of high school courses. The problem of student curriculum planning in the high school has long been left with counselors, administrators, and students. In the past, if any individual guidance was offered at all, the most common method was the school counselor's planning interview with each student. Generally, the counselor would sit down with the student and discuss the student's desires, abilities, hopes and aspirations. They would then proceed to select from the hundreds of courses available to the student. Such an interview would typically last from 15 to 30 minutes, and be scheduled once a semester to plan the following semester's courses. It has been estimated that the case load of the average high school guidance counselor ranges from 400 to 600 students (Parker, 1959; Helling, 1963; National Advisory Council on Education, 1972, p. 3). If we assume that a counselor works for nine months each year and that two planning interviews are conducted with each student per year then between 15% and 48% of the work year is occupied with the task of curriculum planning interviews - not counting time taken up by curriculum scheduling.

One possible consequence of this counselor overload is the acceptance of generalized tracking strategies through the curriculum of the school. These "tracks" become traditionalized into things like a "general curriculum" for less able students and "college prep" for the more able. The notions of more and less able end up being based, at lease in part, on subjective cut points on quantitative measures of aptitude and intelligence. The use of completely objective evaluational criteria would tend to lessen the need for tracking and improve the ability of students to move through

the curriculum at a personally suitable level without rigidly demanding arbitrary assignments to "programs of study."

The problem considered here should be further distinguished from the general high school scheduling problem. Tillet (1975, p. 101) divided the scheduling process into three tasks: The determination of course offerings; the scheduling of teachers to classrooms, and periods; and the scheduling of students to course-sections. The "curriculum-assignment problem" as here defined precedes the scheduling tasks. Here we consider the question: Which of the courses offered by the school are those which will best fit the "judged" needs of individual students? A quantitative model for curriculum would be concerned with these two objectives: the provision of an empirical representation of the high school curriculum, in order to facilitate curricular function and long range planning; and the provision of a system which will generate suggested optimal student plans of study (course assignments) from available test data. The optimizations are based on the quantitatively judged value of the courses offered by the school.

OTHER CURRICULUM OPTIMIZATION TECHNIQUES.

Educational literature is filled with writing about which types of courses are best fitted to different kinds of students to most help them in future life (Broudy, 1971; Hauser, 1972; Hughes & Hughes, 1972; MacDonald, 1971; Saylor & Alexander, 1974; Taba, 1962). Such works have been very general. Seldom has curriculum selection and assignment been quantitatively considered.

The general approach of operations research applications require that:

1. All aspects of the problem space must be quantifiably. Such representations can be made using "perfect" or probabilistic information. This is a particularly difficult requirement for curriculum problems becuase of a generalized lack of problem definition.

2. Some "objective function" must be found which is to be optimized (either maximized or minimized). As we all know verbalized educational objectives are difficult enough to specify. Quantitative objectives are often much more elusive.

3. Operations Research (OR) techniques must exist which can solve the problem in a finite amount of.

time. Not all problems which can be specified will have solutions which will converge in a finite number of iterations. Even after requirements one and two are met we still need a emprical computational technique which solves the problem.

But, there are a number of articles which have treated optimization strategies in other areas of education. One such application is in computer-assisted instruction (CAI) (Atkinson & Wilson, 1969). The introduction of linear optimization models for improving the flow of such instruction is indeed a contribution to improved learning. Dynamic programming (DP) was used by Rothstein (1973) for the selection of journals for a university library. The utility of selected periodicals (expected contacts by readers) is maximized subject to the amount of funds available for acquisition.

For curriculum sequencing, Taft and Reisman (1967) have presented a clean and thorough model for a core curriculum in a college engineering department. Their model uses an objective function based upon a theoretical stochastic function for learning and forgetting. This model optimally orders units of the core curriculum, but does not select courses. The solution process is one of successive replacement of courses until an optimal sequence is found.

For curriculum selection, Page, Jarjoura, and Konopka (1976) have proposed a dynamic programming model. The basic concern of this application is the assignment of levels of study to units of curriculum. Their example optimizes the judged educational benefit of certain levels (intensities) of study of a text (or other structure) requiring a certain number of hours for completion of that level of study. The object is to optimize the judged benefit to the student over all chapters (or units) of the text (or material). Levels of study are selected for each chapter under an overall constraint on the total number of hours allowed for the study of the text. Konopka (1977) has applied this model to several textbooks used in mathematics courses.

The present writer (Grandon, 1974) has proposed a theoretical formulation of the school curriculum assignment problem as here defined, which also makes use of DP solution techniques. I assigned sets of courses to individual students (or types of students). The drawback of that formulation lay in the necessity of generating all of the allowable combinations of courses for each grade. Such a formulation would solve the problem, but the generation of all allowable paths through the curriculum is as yet computationally infeasible. The present research is an extension of that method.

HUMAN CURRICULUM VALUING AND STUDENT CLASSIFICATION.

Curriculum Valuing.

One criticism of operations research applications has been the relative absence of human input into the calculations which are supposed to optimize our environmental and psychological well-being. There have been a few attempts to use psychological objective functions (Taft & Reisman, 1967; Trueman, 1974, p. 119). In scientific research in general, this lack of human valuing has led Kaplan (1964) to conclude that "from the standpoint of the public, the scientist is damned if he takes values into account and likewise damned if he doesn't" (p. 372). Strategies described elsewhere (Grandon, 1974; Tillet, 1975; Page, Jarjoura, & Konopka, 1976; Konopka, 1977) have implemented human values as objective functions to be optimized within the framework of linear and dynamic programming. The quantities which are optimized are human judgments as to value, effectiveness, preference, and performance.

To help us in optimizing, the subjective values of people must be made both overt and quantifiable. This problem has been explored in relation the bentee (Page, 1971; Page & Breen, 1973), to define a measure of "overall educational advancement". Such a measure would be useful in reducing profiles of scores to a single measure. The major point of the technique lies in the use of expert judges to assign weights to various branches of a hierarchy of outcomes. Such a tree is shown in Figure 1 for valuing a high school curriculum. As can be seen, the tree extends from the most general value, down to the more specific course values for departments. With the addition of other branches, the tree could also be extended to section values (within subject), or topic values within courses. It is the job of the judges to fill in all the values appropriate for each student (or type of student) on each branch of the tree. The exact form of the valuing strategy adopted for the present work varies somewhat from this hierarchy, but the analogy holds if we consider that the measure of overall value for a student schedule is a linear combination of the values of the selected nodes. One important contribution of this work is that Page and Breen (1973) have found that pooled judgments tend to correlate highly with each other, yielding reliable measures of value. And here, the pooled judgments of more than one judge are used for the determination of course values.

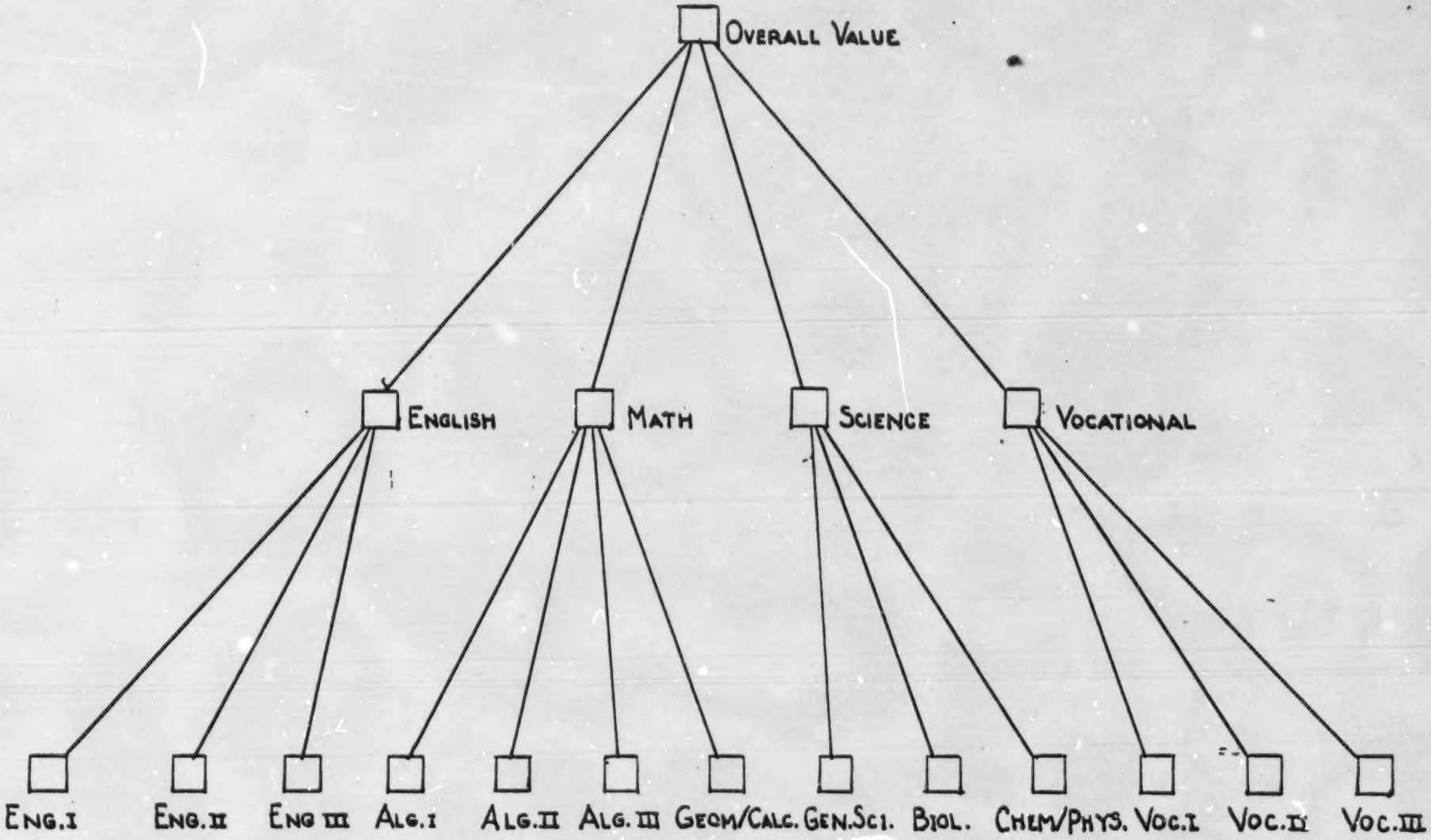


FIGURE 1

A SMALL HIERARCHY OF OUTCOMES TREE FOR VALUING A HIGH SCHOOL CURRICULUM

Student Classification.

The Automatic Curriculum Planning Program (ACPP) can operate in two general modes. The first is for individual students. Here each student would have each course in the curriculum numerically valued according to his or her specific abilities and interests. The system would then generate a plan of study based on these values. The second and far more useful mode for system evaluation and long term planning applications is the "group scheduling" mode. In this mode, groups or clusters of students are treated as individual students. This has the effect of assigning curriculum to the complete set of students based on their derived student grouping. The technique hinges on the determination of cohesive groups of students from empirical information. Once this is done, each group is valued by curricular judges and the plans of study generated by ACPP. A section of ACPP has been implemented which uses linear regression techniques to predict new sets of values for students not included in the original grouping procedure. These values will resemble the student's type values had they been in the grouping process.

Clearly, a portion of the validity of suggested plans of study depends on the accuracy of the initial classificaton of students into "types". Two general types of grouping procedures have been investigated by Grandon (1976, 1978): Q-Factor Analysis and Cluster Anaylsis. The conclusions of this investigation were that when Q-factor analysis is used with fewer variables (measures of performance and ability) than students not as many groups are discovered as may be present in the population. This is due largely to a quirk of matematics concerning factor solutions of matrices where the rank and order are not the same. Inference from these types of solutions may also be poor (Rummell, 1970, p. 220). Hierarchical Cluster Analysis (Ward, 1963) on the other hand yielded very good results.

In order to test the performance of ACPP, a testing site was selected. This was a high school of average size and typical curricular structure. Obviously, the experimental use of students was impossible. Even if student, parents, and administrators had granted their permission, the evaluation would have had to wait for the students' completion of four years of high school. As an alternative, the records from the class of 1975 were used. Permission was obtained to access transcripts of schedules and personal data (e.g. testing information). These students entered the test high school in 1972.

A random sample of one-third of the class was obtained; 100 students from a class of 300. Missing or faulty data reduced the working sample to 95; 44 boys and 51 girls.

Although the sample is from only one location, the types of technical problems met are not substantively different from those in other comprehensive high schools. It is a four-year school with a counseling staff of five. The school is of typical ethnic composition.

Only testing information from the 9th grade was used, so as to simulate the environment of the incoming freshmen. Data collected for each student included: student identification codes, sex, 9th grade Otis-Lennon (1967) Mental Abilities test score, the scores on all four scales of the Co-operative English test (Co-operative Test Division, 1970), the ID code for each course which the student took during his tenure at the high school, and the grade during which each course was taken. At the same time curriculum offerings for the four years were collected.

A multiple analysis of variance (MANOVA) was performed to determine whether the boys differed on these measures (IQ, Coop-vocabulary, Coop-comprehension, Coop-expression). The multivariate F-test using Wilks' Lambda criterion (Cooley & Lohnes, 1971) was highly significant ($p < .001$). The canonical correlation between the four tests and sex was .489. These results indicate a moderate difference in performance among the sexes. It was decided on this basis to treat boys and girls as independent groups of students. Table shows the group means, univariate F-tests and discriminant functions weights.

TABLE 1

Descriptive Statistics by Sex.

Test	Boys(N=44) Means	Girls(N=51)	Univariate F	Discriminant Wt.
IQ	106.32	105.04	.238	.575
CO-VOC	147.23	145.71	.676	1.303
CO-COMP	143.08	146.83	4.028*	-0.914
CO-EXP	141.11	144.59	3.668*	-1.130

*Significant at p<.06 with 1 and 91 degrees of freedom.

Each group of student, boys and girls, was then subjected to hierarchical cluster analysis. After the determi-

nation of an adequate "stopping" criteria for the clustering procedure five "types" of boys and six "types" of girls were discovered (Grandon, 1978). Figures 2 and 3 display the profiles of the boys and girls cluster solutions with all scores standardized to have mean of zero and standard deviation of ten.

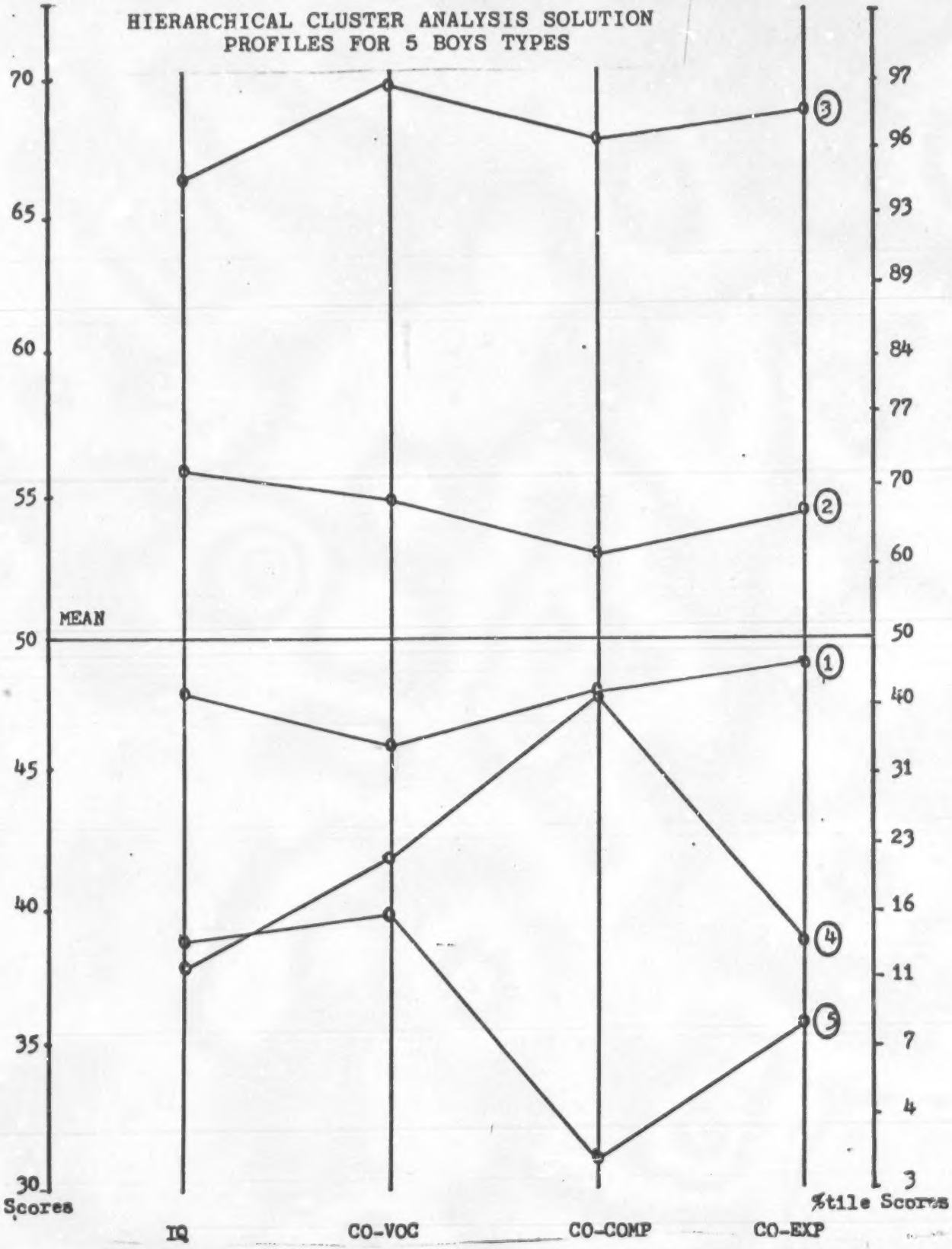
It does not matter to the curriculum model presented here which techniques are used for identifying student types. What does matter is that these types be representative of their respective populations. Certainly the nature of the observations used for student data will influence the optimality of any grouping strategy. Testing information happens to reflect general ability substructures as we see from the nearly parallel lines for student type profiles. Quite probably, if interest inventories had been used, the above classifications of student types would have come out differently.

The Counselor Valuing Task.

The design of this research calls for the course valuing for each student type by a set of high school guidance counselors. It was decided that the student types derived above have specific course values assigned by as many counselors as time and money could provide. Each counselor used for judging was a full-time working counselor in a high school. All five counselors from the test high school participated as well as five others from two surrounding schools. Half of the counselors were male and half female. Each was paid $50.00 for his/her time and service (under a grant from the University of Connecticut Research Foundation).

Each counselor-judge was provided with a complete valuing packet. This packet contained several different forms. The first, a "Test High School Automatic Curriculum Planning Guide", was a comprehensive description of the test high school's curricular offerings. It contained a brief overview of the curricular structure of the school, a description of the five different "levels of instructional difficulty", and an exhaustive description of all courses offered. Judges were also provided with a graphic representation of the student type profiles as in Figures 2 and 3 above. The most important part of the valuing packet was the "Test High School Course Value Form"; one for each student type was included. Attached to each of the 11 Course Value Forms were the "Test High School Student Information Forms", one to further describe each of the student types. Judges were not told that they were assigning values to types of students rather than individuals. This ploy was

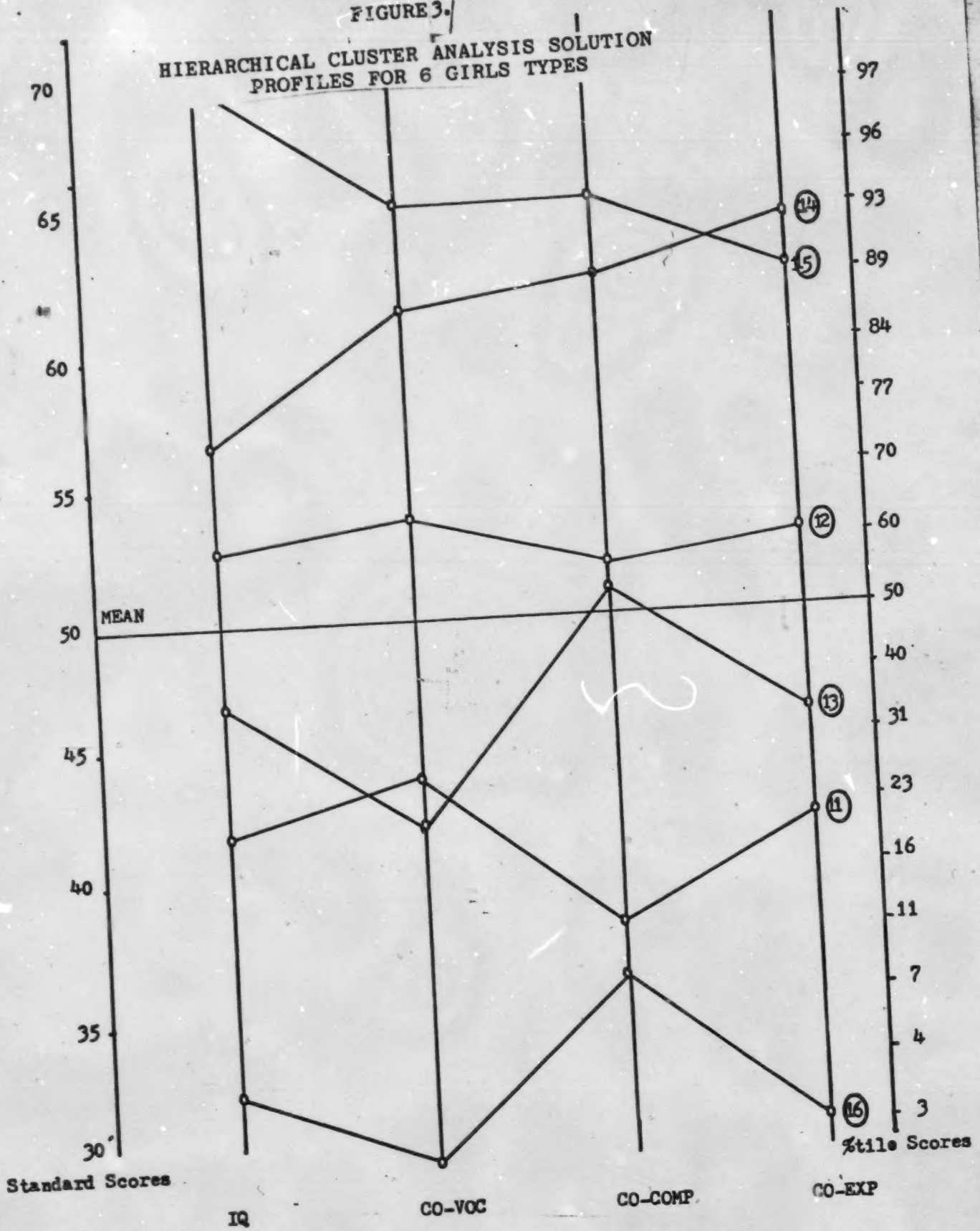
FIGURE 2



NOTE: The left hand scale is in standard scores with mean of 0 and standard deviation of 10. The numbers in circles to the right are group identification numbers.

FIGURE 3.

HIERARCHICAL CLUSTER ANALYSIS SOLUTION
PROFILES FOR 6 GIRLS TYPES



used to enable them to assign value without any prejudice against "computer"-generated student types.

Each Course Value Form contained spaces for the judges to indicate suggested credits for each of the 11 academic departments, the total credits to be taken, a space for each course's numeric overall value, and four spaces for the courses values if it were taken in the 9th, 10th, 11th, or 12th grades. Judges were requested to keep numeric values between 0 and 100.

The Interjudge Reliability of Course Values.

The values used in the generation of curriculum by ACPP are a mathematical manipulation of the values assigned to the courses by judges. A scoring procedure akin to cross-multiplying standardized overall course values, where courses are compared against each other, with specific grade values, where a courses value compared for each grade. Before such manipulations are performed, though, the reliability or interjudge valuing consistency across student types must be determined.

The technique used to measure reliability is from Kerlinger (1973, p. 447). If we consider each score to have some reliability across the 10 judges, each judge can be thought of as an item on a test. We then calculate r-tt for each score using his approach for test items. What we come out with is hundreds of reliabilities. The average reliabilities by aggregated by department are presented in Table 2.

Negative reliabilities are possible in Table 2 when there is some judge-by-student type interaction not equal to zero. This means that judges reactive very differently to some of the student types as regards certain courses. We see that in Music, Art, Physical Education, and Driver Education that interjudge reliabilities are low. These departments contain traditionally non-academic subjects and electives. It is not altogether reasonable to expect counselor-judges to value such course offerings consistently, largely on the basis of academic indicators. Clearly, the testing profile of the student types should include the interests of the students to help with the valuing of these kinds of courses. An alternative to interest inventories would be to have individual students value their own forms. That is to use the "individual" mode of ACPP.

In general, interjudge reliabilities are at very acceptable levels. Some departments which offer courses less related to academic variates, are valued less consist-

TABLE 2

Summary of Interjudge Reliabilities for Departments.

Department	Statistic	Overall	9th	10th	11th	12th
				Grade		
	Mean	.25	.72	.50	.17	-.10
Art	S. D.	.35	.03	.37	.71	.63
	N	17	2	7	10	15
	Mean	.75	.83	.58	.70	.66
Business	S. D.	.12	.10	.23	.17	.18
	N	21	2	8	16	20
	Mean	.91	.94	.93	.93	.87
English	S. D.	.04	.03	.03	.03	.14
	N	31	4	5	5	17
	Mean	.81	.83	.61	.79	.73
Home Econ.	S. D.	.12	.04	.38	.10	.14
	N	17	2	11	15	16
	Mean	.77	.65	.75	.77	.72
Indust. Art	S. D.	.16	.32	.17	.13	.14
	N	13	6	12	13	13
	Mean	.90	.93	.89	.82	.82
Foreign Lang	S. D.	.07	.15	.11	.10	.11
	N	13	9	12	13	12
	Mean	.90	.93	.89	.82	.82
Math	S. D.	.08	.04	.05	.10	.09
	N	16	4	6	9	11
	Mean	.05	.04	.09	-.05	-.01
Music	S. D.	.14	.19	.21	.45	.32
	N	9	6	9	9	9
	Mean	-.44	-.66	-.66	-.46	-.15
Phys. Ed.	S. D.	.22	-	-	-	-
	N	4	1	1	1	1
	Mean	.81	.83	.90	.72	.74
Science	S. D.	.18	.10	.06	.22	.18
	N	16	5	4	7	7
	Mean	.74	.95	.61	.74	.72
Soc. St.	S. D.	.25	.03	.13	.16	.17
	N	13	3	5	10	10
Driver Ed.		.31	-	.30	.40	-.02

Diversified Occupations	.93	-	.72	.87	.91

Note. Tabled N's are numbers of courses. The last two entries are the two non-departmental courses listed singly.

ently than departments which tend to offer more academic courses. The real suprise is the level to which the judges agreed for the Home Economics and Industrial Arts courses. These areas are considered non-academic, but for purposes of scheduling, academic measures tend to be used consistently by all judges.

THE AUTOMATIC CURRICULUM PLANNING PROGRAM (ACPP).

The Automatic Curriculum Planning Program (ACPP) is a computer based algorithm which incorporates both operations research and artificial intelligence (Boolean algebra) solution techniques. Given the very large number of constraints on the solution and the extremely varied curricula of modern high schools, the algorithm is somewhat complicated and at points arbitrary (like the current educational system). Course selections are made for each semester of the curriculum for each of the three or four years of high school. This provides a complete student plan of study at entry to high school based on the curricular valuation of the judges. No attempt has been made to generate every set of optimal student schedules which may reside in the curriculum for a student. This feature could be incorporated at some later time.

The ACPP algorithm is divided into two basic stages. A simple flow diagram is presented in Figure 4. The first stage provides rather complex heuristic information (Nilsson, 1971, pp. 53-54) which "trims" down the number of courses. The second stage generates sequences from the remaining courses and then selects optimal sets of these sequences. The sets of sequences selected comprise the suggested optimal plan of study. Each student (or type) is treated as an independent object and no attempt is made to optimize school resources, only individual plans of study.

Stage One Optimization: Pruning the Tree.

During the Stage One optimization, selections are made from sets of courses of similar interval. These sets are termed "durations". An interval is defined as the minimum unit of curricular time which a course is designed to cover.

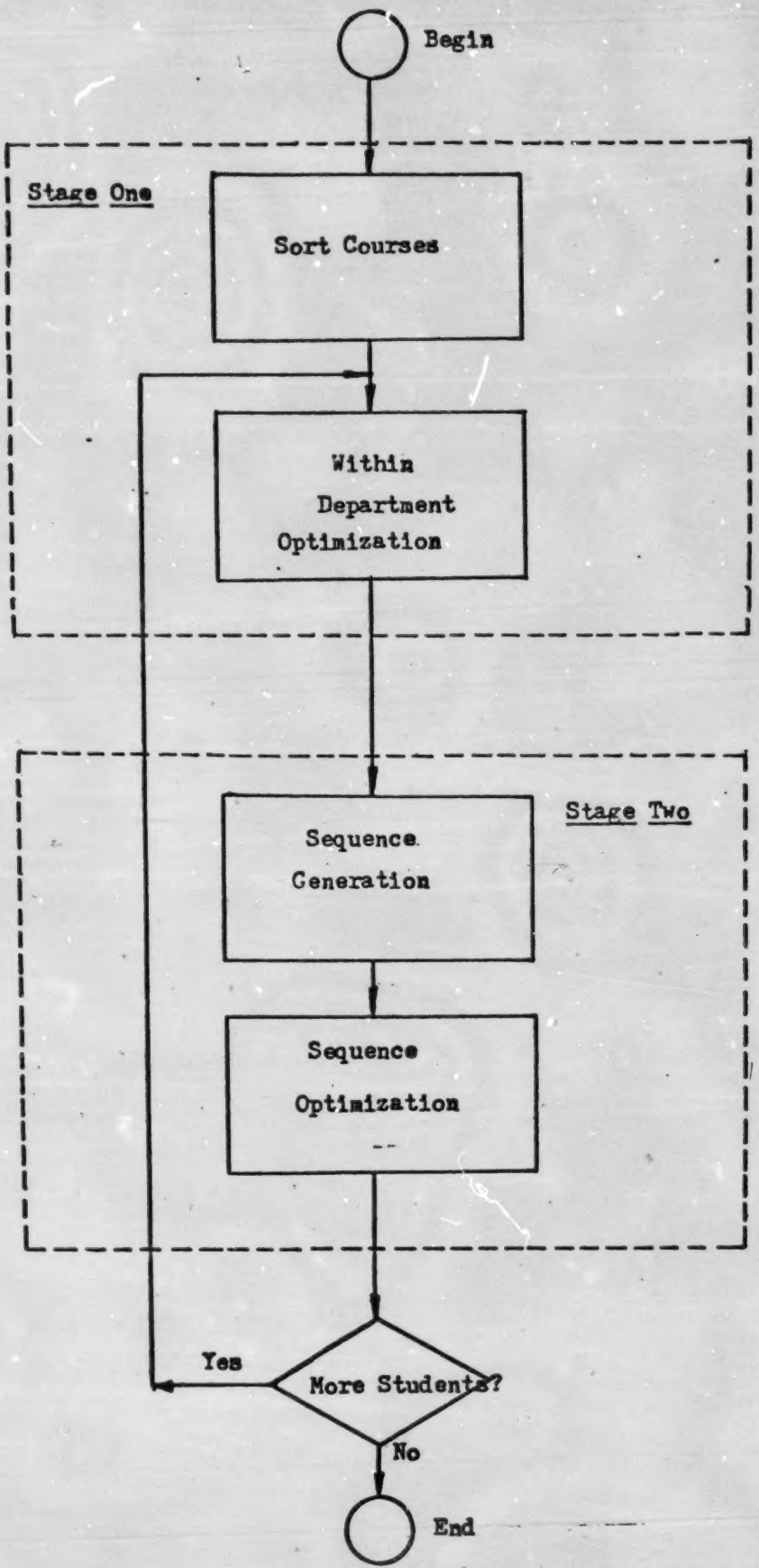


FIGURE 4

The ACPP Algorithm

Some courses may span a whole grade others only one semester. For example, Ceramics and Painting are quarter-year courses, whereas Introductory Art and commercial Art are half-year courses. Ceramics and Painting can be grouped together to become a duration as can Introductory Art and Commercial Art. These intervals become stages for the dynamic programming solutions within each duration. Those courses of highest relative (judged) value are chosen subject to a constraint on the number of credit hours alloted to that duration. Durations are defined within departmental areas. An area is operationally defined as a division from which no two courses may be taken at in the same semester. Before the optimization can be performed courses must be sorted into these durations. This task is represented by the highest box in Figure 4. The credit to be assigned to each duration is calculated as the product of the proportion of total cumulative value for each duration and the credit assigned to that department. Departmental credit assignments are made by the same judges as assign course values.

$$N_i = \text{Credit for Duration} = \frac{\text{Cumulative Value for Duration}}{\text{otal Cumulative Value for Department}} * \text{Credit for Department}$$

We can now make use of the dynamic programming model described by Wagner (1970, p. 254) as the "distribution of effort problem under one constraint". This model is applied to each duration in the curriculum. A graph of the solution space for one duration is presented in Figure 5. As we can see the courses are represented as nodes within each interval of the duration. Our problem can now be formulated as:

$$\text{MAXIMIZE} \quad \sum_{j=1}^{S} B_j(y_j) \quad \text{for each duration of all departments,}$$

Subject to:

$$\sum_{j=1}^{S} H_j(y_j) = N_i$$

$$y_j = 0, 1, 2, \ldots \text{ for each } j,$$

$$H_j(0) = 0, \text{ and}$$

$$\text{each } H_j(y_j) = 0, 1, 2, \ldots \text{ for each } j;$$

Where, y_j represents the selection of the yth course in the jth interval (the y value appears in the circle representing each course in Figure 5), S is the number of intervals in the duration, $B_j(y_j)$ is the value of the course selected by

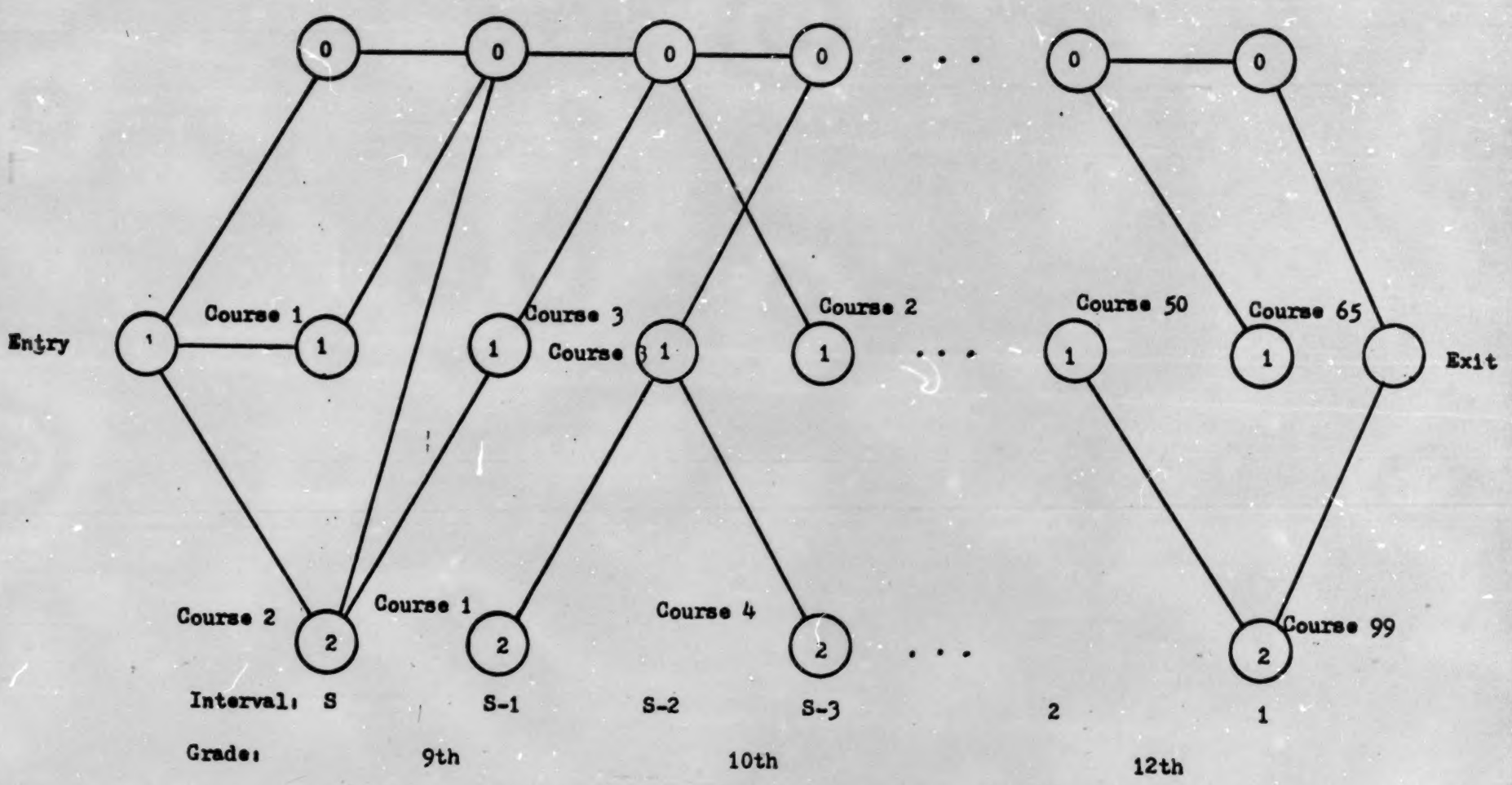


FIGURE 5

Duration Within A Department

y in the jth interval, and $H_j(y_j)$ is the credits for the course selected by y in the jth semester.

We can now define a DP recursion appropriate for the above as,

$$g_j(n) = \text{maximum}(B_j(y_j + g_{n-1}(n-H_j(y_j))) \quad (1)$$

for j = 1, 2, ..., S and $g_o = 0$ for j = 0, 1, 2, ..., N_i. The maximization is only over non-negative integer values of y_j satisfying $H_j(y_j) <= n$ (Wagner, p. 255). Note that it is the overall gain function $g_S(N_i)$ which for which we are looking. The type of solution strategy presented by Wagner for this problem works fine for situations where each course in the network can be reached from any other course in an earlier interval; but as we can see in Figure 5, this is not the case when the network is under prerequisite constraint. The actual solution technique is essentially the same as the tabular method presented by Wagner (pp 255-256) with some changes. A strategy has been adopted which is iterative and converges in varying numbers of iterations, depending upon the structure and values of the duration. The technique is most easily described in five steps.

1. Set j=1 for the first interval.

2. If j=1 after the initial tabular solution then go to step 5.

3. Working from the 12th grade backwards, generate the tabular solution to equation (1) from j to S.

4. Trace back from S, checking for violatiins of prerequisite constraints for each y_j. Upon discovering such a violation at interval j, for example, replace the maximum selection at that interval with the next highest valued course which does not violate the prerequisite constraints of intervals j + 1 to S, and go to step 2.

5. Store the solution for each duration for use in Stage Two optimization.

Stage Two Optimization: Sequence Selection.

Stage One optimization will have greatly reduced the number of courses available for selection during Stage Two. It will also have indicated the semester and grade during which these courses are available. We must now create groupings of these courses, which we will term exclusion groups. These are sets of courses with the following char-

acteristics: (1) They do not violate the selection specifications of Stage One optimization. (2)They do not violate any course sequencing constraints. And (3) they do not violate any prerequisite requirements. These sets of exclusion groups are treated as stages during course sequence optimization. Any course pointing to any other course through prerequisites will constitute a candidate for exclusion-group membership. Separate exclusion groups are created for "required" course groupings.

From the exclusion groups defined above, we now generate all of the permitted combinations of courses within each group. These combinations or sequences will constitute the levels within exclusion group for the sequence optimization. The determination of exclusion groups, and finally the location of sequences of courses within these groups constitute the "sequence generation" phase of the Stage Two optimization as illustrated in Figure 4. A graphic representation of the solution space as now configured is presented in Figure 6.

We can now formulate the sequence selection sub-problem, illustrated in the state diagram of Figure 6, as another "distribution of effort problem under one constraint":

$$\text{MAXIMIZE} \quad \sum_{m=1}^{L} B_m(y_m),$$

Subject to,

$$\sum_{m=1}^{L} H_m(y_m)$$

$$= T(T = \text{total credits for all departments}),$$

$$u_m = 0, 1, 2, \ldots, \text{ for each } m,$$

$$H_m(0) = 0,$$

and each

$$H_m(y_m) = 0, 1, 2, \ldots, \text{ for each } m,$$

where y_m represents the selection of the yth sequence in the mth exclusion, T is the total credits for all departments, L is the number of exclusion groups, $B_m(y_m)$ is the cumulative additive value of the courses in the sequence selected by y in the mth exclusion group, and $H_m(y_m)$ is the sum of the credit hours of the courses in the sequence selected by y in the mth exclusion group. We can now define the DP recursion as:

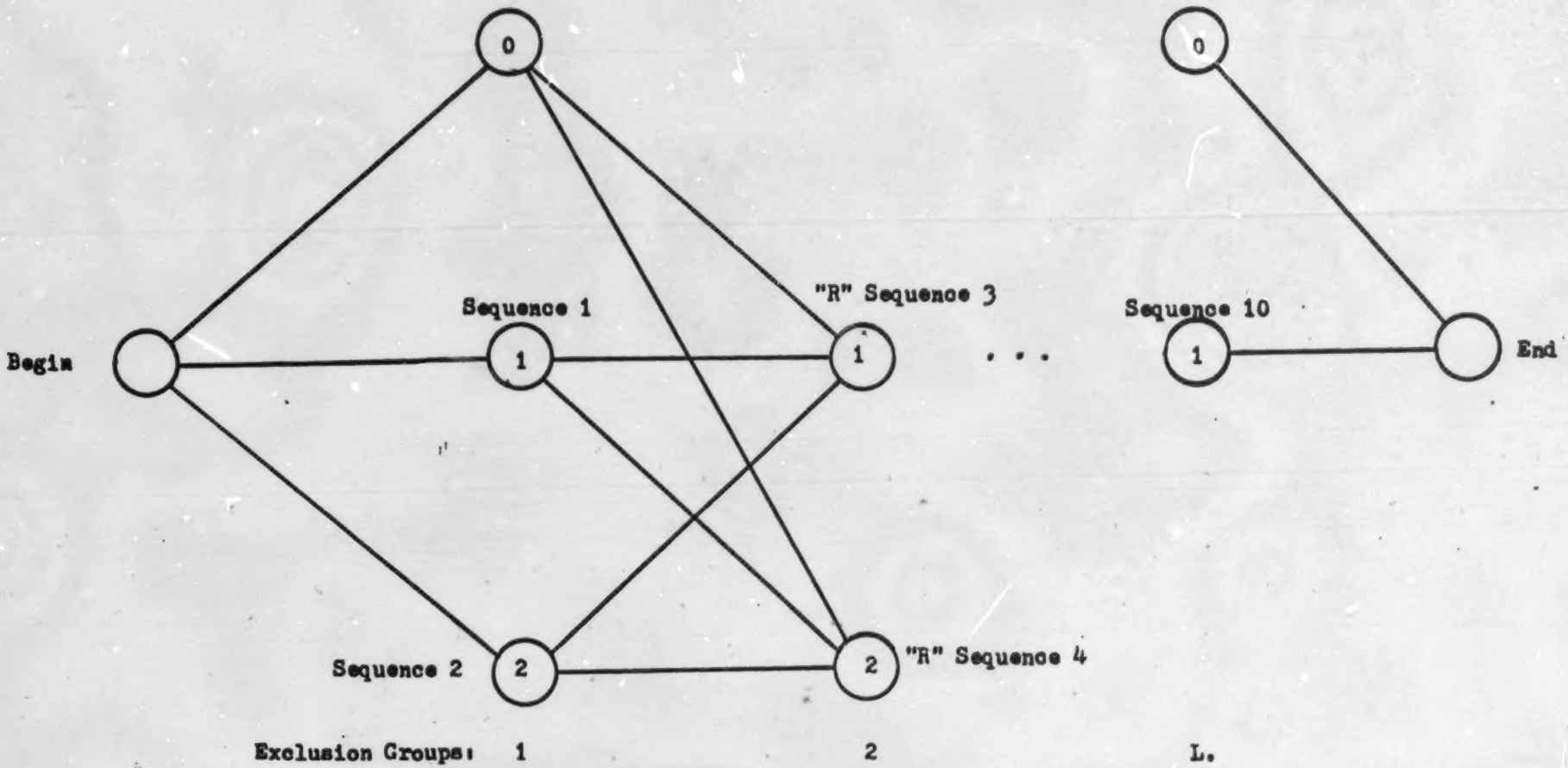


FIGURE 6

The Sequence Selection Sub-Problem.

$$g_m(t) = \text{maximum } (B_m(y_m) + g_{m-1}(t - H_m(y_m))),$$

where t = 0, 1, 2,..., T and the maximization is only over non-negative integer values of y_m which satisfy $H_m(y_m) <= t$. Again we are seeking the overall gain function $g_L(T)$ which will be the total benefit of the student's high school career. Only one special consideration need be made. Allow only maximum credit hour sequences for required exclusion groups. This will insure that all required courses are selected. There are no zero-credit sequences for required exclusion groups.[2]

ACPP'S PERFORMANCE.

Each student was assigned to his type according to the clustering precedure. We then ran ACPP for each student based on the type values. Each of the schedules conformed in every way to the constraints of the test high school. One interesting artifact of the algorithm stemmed from the problem of "tie value" resolution. What should be done when a course is offered in either of two semesters (within a grade) at the same value? This situation is common when values are assigned by grade and not by semester. The algorithm has been designed to quite arbitrarily select the earliest occurance of the course. This results in more courses being selected in the first semester of each grade than in the last semester. A modification of the algorthm could be made to balance this effect. One "quick and dirty" technique would be to use a random number generato' to decide which of the tied values to select.

The degree to which these plans of study vary from "true" optimal is very difficult to assess. Clearly, the Stage One optimization procedure is only "duration-wise" optimal. That is, each duration has been treated independently. This phase is conceived of as providing powerful heuristic information to the second stage of optimization across sequences. Stage Two optimization does not violate any assumptions about the nature of DP, and its solution to the sequencing problem can be considered a "true" optimum. Samples of machine generated plans of study are presented in Figures 7 and 8.

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[2]ACPP has been implemented as a 4,000 line PL/I program. For the present test - a school with 170 courses, 11 departments, 4 semesters per grade, and 4 years of school - the program used 600K of core on an IBM 360/65. Details of the ACPP control language and more information about the code are available on request from the author.

Figure 7. ACPP generated schedule for the highest level boys of Type 3.

THESE ARE THE COURSES SELECTED

NAME	SECNAME	IDCODE	CREDIT	PREREQ
OTHER ART 1	ADVANCED	6911	0.25	NONE
ALGEBRA I	ADVANCED	113	1.00	NONE
BUS. MACHINE I	STANDARD	418	0.25	(111/112/113/115)
GEOMETRY	H.HONROS	123	1.00	(111/112/113)
ADV. ALGEBRA II	H.HONORS	133	1.00	(123/122/121)
MATH 12 ACCELERATED	H.HONORS	144	1.00	(133/132/131)
ENGLISH 9	HONOR	12	1.00	R
ENGLISH 10	H.HONORS	21	1.00	R(012/013/014/015)
ENGLISH 11	H.HONORS	31	1.00	R(021/022/023/024/025
SPEECH/DRAMA	HONORS	905	1.00	R(031/032/033/034/035
DRAMA 2ND	HONORS	472	0.50	NONE
FRENCH I	STANDARD	51	1.00	NONE
FRENCH II	ADVANCED	57	1.00	(051)
FRENCH III	HONORS	58	1.00	(057/052)
SPANISH I	STANDARD	61	1.00	NONE
SPANISH II	ADVANCED	62	1.00	(061)
SPANISH III	HONORS	63	1.00	(062)
CHORAL MUSIC I	STANDARD	7011	0.50	NONE
PHYSICAL ED. I	STANDARD	811	0.25	R
PHYSICAL ED. II	STANDARD	821	0.25	R(811)
PHYSICAL ED. III	STANDARD	831	0.25	R(821)
PHYSICAL ED. IV	STANDARD	841	0.25	R(831)
DRIVER EDUCATION	STANDARD	9901	0.25	NONE
BIOLOGY ACCEL	H.HONORS	211	1.00	NONE
CHEMISTRY ACCEL.	H.HONORS	221	1.00	(211)
PHYSICS ACCEL.	H.HONORS	231	1.00	(221)
MINI SCIENCE 1ST	ADVANCED	290	0.25	A4(211/222/212/249)
SOCIAL STUDIES 1	HONORS	311	1.00	R
ECONOMIC GEOGRAPHY	ADVANCED	392	0.50	(311/312/313)
SOCIAL GEOGRAPHY	ADVANCED	391	0.50	(311/312/313)
SS 4 SOCIAL CHANGE	ADVANCED	342	0.25	(311/312/313)
SOCIAL STUDIES 3	HONORS	331	1.00	R(311/312/313)

TAL NUMBER OF COURSES= 32
AL NUMBER CREDITS= 23.25
TAL VALUE= 2873.138
UE PER CREDIT= 123.576

Figure 8. ACPP generated schedule for the lowest level girls of Type 16.

THESE ARE THE COURSES SELECTED

NAME	SECNAME	IDCODE	CREDIT	PREREQ
BASIC CRAFTS 1 CRED	BASIC	6132	1.00	NONE
BASIC CRAFTS 1ST	BASIC	6131	0.50	NONE
INTRO TO ART	BASIC	612	1.00	NONE
INDEPENDNT STDY 2ND	HONORS	6381	0.50	(612)(6131/6132/630/632/635/636/623/63
FASHION DESIGN 1ST	ADVANCED	6341	0.50	(612)
CERAMICS 1ST	ADVANCED	635	0.50	(612)
OTHER ART 1	ADVANCED	6911	0.25	NONE
TYPING I	STANDARD	436	1.00	NONE
DATA PROCESSING I 1	ADVANCED	424	0.50	(436)
GENERAL BUS TRNG	STANDARD	412	1.00	NONE
GENERAL MATH I	BASIC	115	1.00	NONE
BUS. MACHINE I	STANDARD	418	0.25	(111/112/113/115)
ENGLISH 9	BASIC	15	1.00	R
ENGLISH 10	BASIC	25	1.00	R(012/013/014/015)
ENGLISH 11	BASIC	35	1.00	R(021/022/023/024/025)
ENGLISH 12	BASIC	45	1.00	R(031/032/033/034/035)
DRAMA 2ND	HONORS	472	0.50	NONE
INTRO TO CLOTHES	ADVANCED	513	0.50	NONE
INTRO TO FOODS	ADVANCED	511	0.50	NONE
INDIVIDUAL & SOCITY	STANDARD	547	1.00	NONE
HOME MANAGEMENT I	ADVANCED	526	0.50	NONE
CHORAL MUSIC I	STANDARD	7011	0.50	NONE
PHYSICAL ED. I	STANDARD	811	0.25	R
PHYSICAL ED. II	STANDARD	821	0.25	R(811)
PHYSICAL ED. III	STANDARD	831	0.25	R(821)
PHYSICAL ED. IV	STANDARD	841	0.25	R(831)
DRIVER EDUCATION	STANDARD	9901	0.25	NONE
BASIC BIOLOGY	BASIC	212	1.00	NONE
SOCIAL STUDIES 1	BASIC	313	1.00	R
SOCIAL STUDIES 3	BASIC	333	1.00	R(311/312/313)

TOTAL NUMBER OF COURSES= 30
TOTAL NUMBER CREDITS= 19.75
TOTAL VALUE= 2745.277
VALUE PER CREDIT= 139.001

Now we can compare the overall values of schedules generated for student types with those that the students of the those types took. In general, more credits were suggested by counselor-judges than were originally taken by students in our sample. This means that without some correction for the number of credits selected, a simple additive dependent measure of overall course value would be unduly biased in favor of ACPP. By using the ratio of the additive value to the number of credits in each of the two schedules, this bias is removed. Values used to rate the original student schedules are the same counselor-judge values used to determine the ACPP generated schedules. Basic statistics for the 95 students on each of the dependent measures are given in Table 3.

TABLE 3

Basic Statistics for each of the Two Schedules.

Measure	Mean	Standard Deviation	N
PP Scheduling	128.659	5.869	95
Original Scheduling	105.731	7.238	95

As we can see from Table 3, ACPP scheduling yields schedules more highly valued than those actually taken. These means can be contrasted by the use of a one-way, repeated-measure analysis of variance (Myers, 1975, p. 167). This analysis yields an F-ratio of 591.413 ($p<.00001$ with 1 and 94 degrees of freedom) for the effect of scheduling.

bviously, when the type values are used the computer technique results are very superior. And there is approximately a 20% "improvement" over traditional scheduling techniques. Given the assumptions, then, the algorithm fared well in the competition with the original "human" techniques. It is well caution though, that not too much should be made of this comparison. Students in the normal course of schooling often differ from the best advise of their counselors. This fact is confounded in our above contrast. But even yet, the performance of ACPP is very encouraging.

SUMMARY AND CONCLUSIONS.

The findings of this study indicate that quantitative models for decision making can prove useful in the selection of courses for high school students. These present selections are based on student groupings derived from sex and test performance. In other applications of this model, a wider variety of data on students should be available and useful, such as measures of academic interest. In principle, any measure of personality or background might be suitable for grouping purposes.

Furthermore, it is possible to generate optimal plans of study for students whose type values were not obtained. Predictions of such values have been made using multiple regression, as reported by Grandon (1978). This technique generates a "black-box" prediction model which consists of hundreds of regression equations (170 courses times four grades of school). Such predicted values can also be optimized by ACPP, and new individualized plans of study created. Four-year suggested plans of study can then be generated for an entire student body at entrance to high school. These plans could be used during student-counselor interviews to give, for the first time, a representation of student quantitative performance (tests, interests, etc.) in terms of actual course selections. High school administrators might have several years notice that certain areas of their curricula were going to be highly requested or that other areas might be declining in enrollment.

Adaptations of ACPP can be made for use by individuals. We may imagine an interview between student and counselor taking place at a computer terminal. The machine may have available the student's relevant quantitative data, and may display an initial plan of study. Counselor and student discuss discrepancies between this proposed plan and some ideal. Perhaps more science is desired - so an adjustment is made in the credit constraint for the Science Department, and a new plan is displayed. This process may iterate as often as seems useful. Granted, such an application may now seem visionary but current changes in costs of hardware may make such a scenario much more realizable.

In summary, we have defined a quantitative model for the assignment of curriculum to students. It can be based on the judged meaning of quantitative measures of student performance. Such an approach to course selection eliminates the need for tracking in our schools when used with the statistical value generation techniques described briefly above. The model can be used for assigning courses to all students at once, or exploring individual options. Such tools should prove useful as stepping stones toward more rational curricular design and selection. In educa-

tion, now the largest single enterprise in our economy, the gain in financial efficiency may be well worth our attention, not to mention the less tangible benefit from improving the school experience.

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